AIAA 98-0912

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36th Aerospace Sciences Meeting & Exhibit
January 12–15, 1998 / Reno, NV

A Stochastic Approach to Multi-disciplinary Aircraft Analysis and Design

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Abstract

Within the context of multi-disciplinary aircraft analysis and design, a new approach has been formulated and described which allows for the rapid technical feasibility and economic viability assessment of multi-attribute, multi-constrained designs. The approach, referred to here as Virtual Stochastic Life Cycle Design, facilitates the multi-disciplinary consideration of a system, accounting for life-cycle issues in a stochastic fashion. The life-cycle consideration is deemed essential in order to evaluate the emerging, all encompassing system objective of affordability. The stochastic treatment is employed to account for the knowledge variation/uncertainty that occurs in time through the various phases of design. Variability found in the treatment of assumptions, ambiguous requirements, code fidelity (imprecision), economic uncertainty, and technological risk are all examples of categories of uncertainty that the proposed probabilistic approach can assess. For cases where the problem is over-constrained and a feasible solution is not possible, the proposed method facilitates the identification and provides guidance in the determination of potential barriers which will have to be overcome via the infusion of new technologies. The specific task of examining system feasibility and viability is encapsulated and outlined in a series of easy to follow steps. Finally, the method concludes with a brief description and discussion of proposed decision making techniques to achieve optimal designs with reduced variability. This decision making is achieved through a combined utility theory and Robust Design Simulation approach.

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Paper presented at the 36th Aerospace Sciences Meeting & Exhibit, Reno, NV, January 12-15, 1998

Definitions

Since many of the topics discussed in this paper represent concepts with which the reader may not be familiar, a few key definitions are offered for clarity:

Ambiguity: The un-described and vague (linguistically) portion of a design [1]. Ambiguity occupies the space complement to knowledge.

Conflict: Conflict occurs when an objective cannot be extremized to the greatest possible degree since such a strategy would cause other effects that would result in a degradation of the objective [2].

Decision Maker: Someone (a professional), or a team of professionals, who has authority to allocate resources and has responsibility for the output decision.

Decision Making: An intelligent activity aimed at allocating resources in order to develop a system to meet the customer's expectations and requirements.

Decision Support: A methodological and technical environment which facilitates the decision making process.

Fast Probability Integration (FPI) [3, 4, 5]: A family of probabilistic analysis techniques characterized by better efficiency and transparency rather than "brute force" probabilistic techniques such as the Monte Carlo (MC) Simulation.

Feasible Alternative: A design alternative which satisfies all imposed constraints (i.e. it is physically realizable).

Metamodel: An approximation of a complex analysis model. Typical metamodels include regression models of complex computer programs based on experimental designs (e.g., the Response Surface Method), artificial neural networks, fuzzy sets, or other metamodel building methods [6, 7].

Metric: A Figure of Merit that characterizes a discipline or function or their related technologies (e.g., L/D for aerodynamics or SFC for propulsion).

Probabilistic Analysis: Analysis which allows for the examination of systems with imprecise or incomplete information (i.e., uncertainty and ambiguity). In other words, a means of forming relationships between input and output variables, including the variability of the inputs.

Risk: Risk can be defined as the probability or chance of achieving an unfavorable outcome.

Robust Design: A design which is least sensitive to influence of uncontrollable factors. A solution that optimizes affordability while reducing associated variability.

Stochastic Process: Uncertain history of response over the range of time values.

Subjective probability: A probability which has no specific definition but is based on experience, expert opinion, intuition, or educated guesses.

Uncertainty: An estimate of the difference between models and reality. Uncertainty is manifested when quantities associated with the product can not be determined exactly, and is a term describing the imprecision in establishing the value of a variable.

Viable Alternative: A design alternative which is feasible and meets or exceeds the customer objective(s) (i.e., it is physically realizable and affordable).

Virtual Design: Assessment of real-time interactive computer simulation of physical interactions in engineering systems.

Introduction

The engineering design community is presently in the midst of a *paradigm shift*. Recent initiatives in government and industry, focused on system *affordability* as the overall decision making objective, are defining and encouraging this shift, and have provided the motivation and framework for the research presented in this paper.

The selection of affordability as the design driver denotes a dramatic change in the mindset of how complex systems are designed and built today. "*Design for Affordability*" implies that the design and evaluation of a system is no longer dictated solely by mission capability requirements, or even product characteristics. Instead, it is a robust decision making design process that balances mission capability with other system effectiveness attributes, while keeping cost under close attention. This balance between benefit and cost is the main foundation of Design for Affordability, and it may be viewed simply as a measure of value, represented as the ratio of benefits provided or gained from the product or service to the cost of giving or achieving those benefits.

In addressing Design for Affordability, the designer must develop the system by accounting, from the outset, for its life-cycle behavior, and allowing for trade-offs in decision making between the various attributes that comprise operational effectiveness. A designer must further distill information about these potential solutions using ambiguous product requirements definitions, incomplete data models, and under the pressures of time and budget constraints. In most cases, cost must be reduced or kept under control without degrading the effectiveness of the system. In order for this to be achieved, the designer must gain a clear insight as to the impact that his/her decisions have on the various attributes and the associated cost. In addition, due to the reduced budgets and number of new designs studied, the opportunity for expensive flight test programs is also reduced. Hence, the design must be able to accomplish these without the resource of historical databases. This "dilemma" is perhaps best illustrated by Figure 1. For new complex systems, the design team is asked to make decisions in the early phases of the process, with relatively minimal knowledge which constrain the configuration, reduce the design freedom, and greatly affect the costs committed.

The variation of design knowledge, design freedom, and cost commitment as a program proceeds through the various design phases are depicted in Figure 1. Inspection of this figure shows that design freedom rapidly decreases, while the knowledge about design is slowly increasing, and that cost commitment (life cycle) gets locked in early. This is particularly true for complex engineering systems. To remedy this situation, a design process is desired which brings more knowledge to the earlier product development design phases, where leverage is greatest, keeping the design freedom open longer; and shifting to a more gradual cost commitment curve, ideally following the trend of how cost is expended.

The authors' current ideas on how to facilitate this paradigm shift from deterministic, performance based multi-disciplinary design to a stochastic formulation whose goal is maximizing affordability are the focus of this paper. The framework for a new stochastic design methodology which accounts for uncertainty, and incorporates physics-based disciplinary analysis, has been formulated and is presented here. This approach is characterized by its use of metamodels to generate higher fidelity, physics (or process) based information to pass on to a sizing and synthesis tool that has the central role of the integrator in the multi-disciplinary design formulation. The incorporation of vehicle economic and operational dynamics, combined with a time varying probabilistic algorithm, and the employment of advanced decision making techniques in searching for affordable designs, complement this physics-based sizing and synthesis tool to form Virtual Stochastic Life Cycle Design (VSLCD).

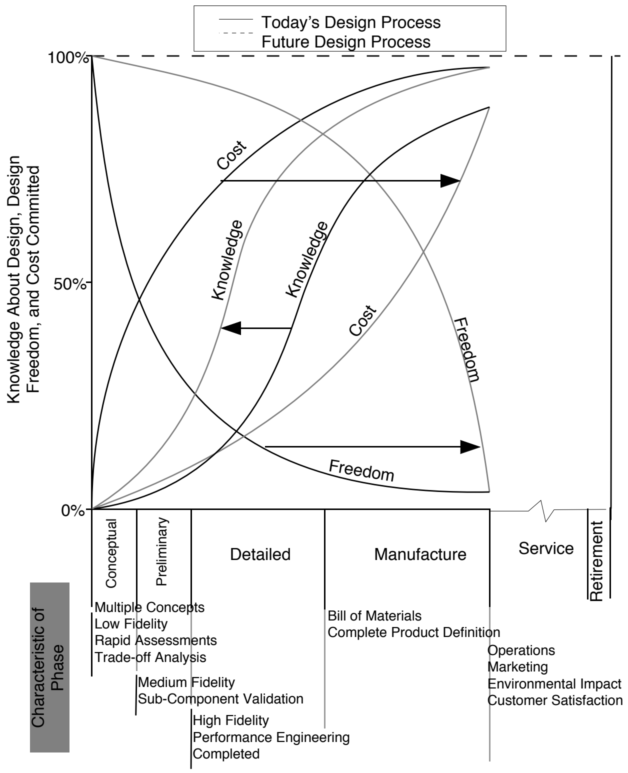


Figure 1: Life-Cycle Design Stages

Critical Issues Associated with Affordability

Affordability does not imply low cost, instead it is a measure of a system's overall effectiveness which calls for a balance between a system's effectiveness and the operational cost associated to provide those benefits. As an example, the attributes of a military aircraft system may be categorized as illustrated in Figure 2.

With this representation of the attributes in mind, an inclusive metric for system effectiveness is its *Affordability* and may be defined as the ratio of:

$$Affordability = \frac{Operational\ Effectiveness}{Cost\ of\ Achieving\ This\ Effectiveness} \quad (1)$$

In order to identify the disciplines/sciences needed to measure and predict affordability, one must examine all of the key attributes which contribute to system effectiveness. Therefore, system effectiveness can be formally defined by:

$$System\ Effectiveness = k_1(Capability) + k_2(Survivability) + k_3(Readiness) + k_4(Dependability) \quad (2)$$

The metric coefficients, $\boldsymbol{k_i}$, provide the ability to tailor this effectiveness to specific needs, preferences, or points of view of a customer. These attributes are directly linked to the traditional product and process disciplines such as aerodynamics, structures, propulsion, signatures, manufacturing, and supportability. The cost associated with achieving this effectiveness may be defined to be the acquisition, or procurement cost, RDT&E, etc., as depicted in Figure 2, or the all encompassing Life-Cycle Cost.

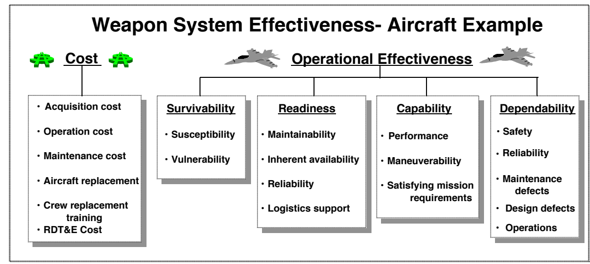


Figure 2: Weapons System Effectiveness [Adapted from Ref. 8]

Life-Cycle Multi-Disciplinary Design

As discussed previously, budget requirements have forced a paradigm shift from design for performance to design for affordability. This shift calls for new, revolutionary concepts outside the traditional, historical databases, and demands the consideration of all life-cycle associated implications. The life-cycle of a product can be defined by a number of discrete phases through which the product proceeds from concept formulation to retirement. For example, an aircraft system, similar to any other complex engineering systems, undergoes the phases of Conceptual, Preliminary, Detailed, Manufacture, Service, and Retirement. Engineering design deals explicitly with the Conceptual through Manufacturing phases while respecting complete life-cycle implications. Each phase has a considerable impact on the product as in Figure 1 [9]. It is evident, though, that the most leverage may be found during the early phases of design. Making educated decisions (increased knowledge) early on, and maintaining the ability to carry along a family of alternatives (design freedom) is the key to success for the aforementioned paradigm shift. The use of modeling and simulation, of course, is a prime example of a way to shift knowledge forward and to capture parametric definitions of the design space.

In many ways, this paradigm shift may be viewed as a natural extension of the ongoing research conducted in the field of Multi-disciplinary Analysis and Design Optimization (MDA/MDO). As the term implies, MDA/MDO deals with the analysis and optimization process of multi-disciplinary problems. In this formulation, an objective is identified, subject to a set of constraints, along with a set of design variables, which are varied so as to yield an optimum solution. Since these elementary parameters often arise from

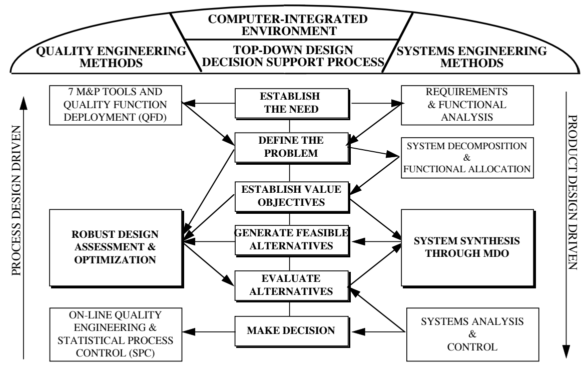


Figure 4: Key Elements Needed for IPPD

Figure 3: IPPD and MDO

requirements may be stated ambiguously, especially in the initial development stages. Proper representation requires the identification, understanding, modeling, and translation of life-cycle customer requirements including market considerations to the design functions.

The un-described and vague (linguistically) portion of a design is the ambiguity that is present [13]. Ambiguity occupies the space complement to knowledge as in Figure 5. Uncertainty arises because quantities associated with the product cannot be determined exactly and the knowledge curve boundary is unknown.

Emphasis is placed here on measuring, quantifying, and integrating customer and market inputs with technological considerations to develop innovative technologies, and design optimal products. Techniques such as Natural Language Processing, intelligent modeling and control through soft computing, possibility models, and conflict identification methods are some of the approaches proposed in literature.

Model Fidelity Representation

A multi-disciplinary treatment of design for affordability calls upon the integration of various analytical methods (implemented as computer codes) at different stages of the design life-cycle. The fidelity of these codes is generally not equal nor known. Another form is introduced as a consequence of inadequate analytical models or the dynamic nature of a system (such as the evolution of a design as it progresses from conceptual to detailed design). Even in the best of circumstances, the uncertainty associated with these estimates is not well known. In such cases, the statistics are unknown. Therefore, fidelity must be determined along with relationships which link the error to operating conditions.

Design and Operational Uncertainty

Design uncertainty is an inability to analytically predict the outcome of an event, or the exact value of a parameter. Operational uncertainty arises as a result of what are often called *noise* parameters that affect the performance of a system. Hence, two distinct classes of design parameters emerge: *control* parameters and *noise* parameters. Control parameters are items that the designer has direct control over, while noise parameters are items that effect the design, but are beyond the control of the designer. Hence, they should not be set to a single point value. Instead, they should be specified in terms of a range and probability

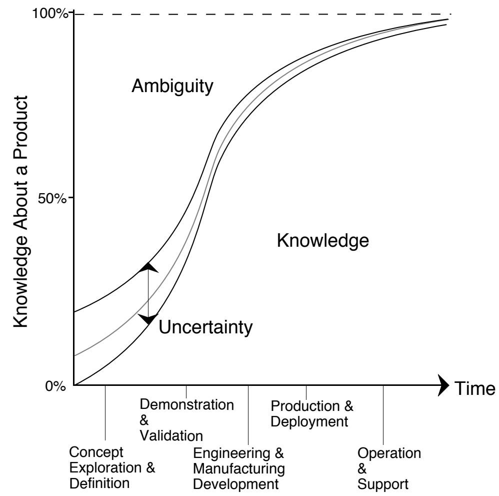


Figure 5: Uncertainty Variation in Time

distribution. This variable distinction follows Taguchi's definitions [15]. Means are needed to analytically quantify and control design uncertainty in multi-objective design problems to yield *robust* designs. This can be facilitated by emerging techniques from mathematics and soft computing disciplines.

Stochastic Nature

The predicted forecast response of some Overall Evaluation Criterion (OEC) is depicted in Figure 6. As indicated in the figure, during the conceptual phase, the distribution associated with such an OEC has significant variability but barely meets the target. As the design process progresses in time through the preliminary and detailed phases, the knowledge about the design progressively increases. This can be seen by the shrinking variability. Furthermore, a shift of this distribution closer to the target is desirable and pursued. This time or design phase dependency with uncertainty dictates the need for a stochastic treatment.

Early in the program, the predicted OEC estimate is well removed from the selected target and has skewed probability distribution. As the program becomes better refined and the OEC estimate shifts closer toward the cost target, the probability distribution shifts to more of a normal distribution. This example has a close analogy to process capability indices, C_p and C_{pk}, used in on-line manufacturing to reduce defects. Hence, on-line robust manufacturing techniques, such as the use of process capability indices, also have a place in off-line manufacturing, i.e. the design phase.

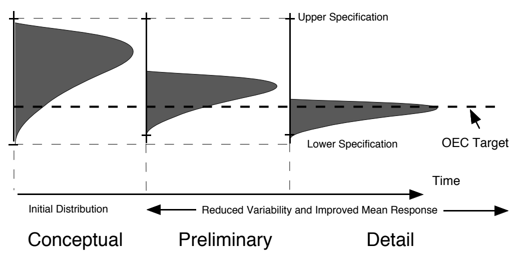


Figure 6: Variability of Design in Time

Multiple Attribute Decision Making

Multiple attribute decision making (MADM) refers to making decisions in the presence of multiple, usually conflicting, criteria. For the case of design for affordability, the decision maker is asked to trade-off survivability, capability, dependability, and readiness. for a variety of scenarios. For instance, optimize the aforementioned attributes, while minimizing or keeping cost fixed at a given level to obtain a configuration that satisfies minimum acceptance levels. Another scenario includes keeping cost fixed while performing trade-offs for the various attributes so as to obtain an optimal level of the OEC. This is performed by placing subjective weight factors in front of each attribute (Eq. 2). For cases where uncertainty is included, the process must also consider solutions or decisions that are robust, i.e., compromised solutions that reduce the associated variability. The distinguishing feature of MADM is then to select the best of a finite number of design solution alternatives. These alternatives have an associated level of achievement for the attributes based on which the final decision is to be made. The final selection of the alternative is made with the help of inter- and intra-attribute comparisons. The comparisons may involve explicit or implicit tradeoffs [16].

New Methodology Formulation

Design, in the context of this paper, can no longer be viewed as a deterministic process. In fact, a probabilistic approach is needed where ranges and shapes for all contributing inputs are available either objectively, when the statistics are known or subjectively, "fuzzy probabilistics", when data is unavailable and ranges are determined based on expert opinion. Realizing that uncertainty varies with time, as knowledge increases about the design (Figure 5), it becomes evident that a time varying probabilistic problem needs stochastic treatment.

A key assumption in the decision making paradigm is that a designer will make the "best" decisions with the knowledge available about a product at the time the decision is to be made. This corresponds to the leftward shift in the knowledge vs. freedom curve in Figure 1.

The central element in the proposed method is a framework for modeling aerospace systems in a stochastic fashion, adhering to the following principles: *physics-based analysis* with associated metamodels are needed to replace relationships based on historical databases (which are likely to be obsolete for current and future vehicles and subsystems). The behavior of the system's entire *life-cycle* must be represented in synthesis and optimization models, and *uncertainty* must be incorporated and mitigated. This framework is shown in Figure 7 and is called Virtual Stochastic Life-Cycle Design (VSLCD). Traditional aerospace design frameworks often stop after synthesis/sizing and optimization. This practice is unacceptable in the emerging paradigm where non-deterministic models and objectives are potential sources of system variability which can affect design decisions. VSLCD addresses this problem by incorporating all phases of design via a *virtual* life-cycle model.

The purpose of VSLCD is to facilitate decision making (at any level of organization) to reach affordable conclusions with adequate confidence. The "VLC" in VSLCD implies that it eventually will encompass in a virtual manner the entire life-cycle including design, engineering development and testing, manufacturing, flight test, and an operational simulation (which will include certification, testing and evaluation, fielding of a vehicle in the existing infrastructure, and tracking of its impact on the economy, market demands, environment, etc.). The word stochastic has been added to VSLCD to indicate that, in the presence of possibly time-varying uncertainty, the method will define, mitigate, and control variability via stochastic methods (e.g. probabilistic, fuzzy, etc.). This capability will enable the designer to assess a design with a high degree of confidence.

VSLCD deals with the processes of using analyses in sizing, synthesis, mission simulation, and eventually in assisting a designer in making decisions. As mentioned previously, these tasks are complicated by elements such as ambiguous customer requirements, operational uncertainty, and technology risk. A primary goal is to understand the nature and variety of design uncertainty and to find ways to analytically quantify and control uncertainty in multi-objective design problems.

A VSLCD capability will enable a designer to assess a design with a corresponding confidence estimate. Customer requirements are translated into metrics that are better defined in engineering terms, and they may change during the design/development process. Operational/environmental uncertainty relates

Figure 7: Virtual Stochastic Life-Cycle Design (VSLCD)

synthesis will allow life-cycle disciplines such as economics and support to be addressed.

Decision Support: Utility is a high-level metric that allows a designer to measure progress and efficacy of candidate solutions. A decision support environment provides design guidance as design alternatives are explored along alternate decision paths.

Integration: Simulation is critical to the determination of product characteristics. Agent technologies and metamodeling facilitate the variety of analysis methods. In addition, advanced data structures being developed that allow stochastic parameter information to be tracked in addition to traditional deterministic values.

Decision Making: Feasible and viable designs are determined through a five step process. Robust Design Simulation will yield robust concepts. Probabilistic methods are employed to capture the influence of code fidelity, operating uncertainty, and requirement ambiguity. Finally, utility theory is used to facilitate multi-attribute decision making, used to weight potentially conflicting requirements.

The summation of the research being conducted in these areas leads to more affordable systems because a comprehensive decision-making strategy has been utilized. More detail will be provided for these areas in the following sections.

Problem Formulation

At first, any design methodology has to formulate the design problem in a formal, possibly, mathematical fashion. Hence, information about the design problem needs to be incorporated in a procedure which yields a decision as to the best design. As shown previously in Figure 5, the typical design problem has three types of information: ambiguous, uncertain, and deterministic. While the deterministic information can be treated with the standard engineering models, such as design and analysis codes, there are no tools readily available to handle uncertain and ambiguous information in design. Methods of addressing this information include Fuzzy Logic which is most suitable for the ambiguous information, and Probability Theory, which most suitable for uncertain information [18,19]. The methodology introduced in this paper concentrates predominantly on uncertain information, which is captured through random variables.

If the actual value of a design variable is unknown, but there exists some knowledge about the design space, i.e. sample space, it can be modeled as a random variable. This is typically called *noise variable* [13] and is associated with operational uncertainty. In addition to the uncertain information about the value of a design variable, the accuracy of an objective function value, modeled by computer simulation or any other engineering model, can also be quite uncertain too. This type of uncertainty is referred to as *fidelity*, and is a typical problem in models based on historical data. Fidelity can be modeled with an error term ε that is added to the objective function value [20]. ε is a random variable with a standard normal distribution. A third type of uncertainty arises through the inclusion of information about the readiness of new technological concepts and their associated risk into the design process. This information can also be modeled with random variables by recognizing the uncertain value of the metric in question, and assigning an appropriate distribution to that metric [21]. The result of the analysis in all three cases will be a probability distribution for the objective function. This distribution is then used in the robust design evaluation.

It is noteworthy here, that the information modeling described above is somewhat tailored to the physics based modeling. If no such analysis tools are available, more generic methods have to be used to capture and formulate the customer requirements of a design problem. Suitable for those problems are such techniques as ‘Seven M&P Tools’ [22] and QFD [8]. These techniques process the information from the customer requirements directly into an OEC, which consists of a weighted sum of the aircraft’s attributes. Then a decision as to which is the best design can be made immediately through an OEC value comparison. However, no analysis is involved in this process and only very little information about the design solution can be produced.

In doing so, the “voice of the customer” can be translated to the objectives through such desires as: reduction in cycle time, lower cost of ownership, dramatic improvements in product quality, reduced overall life-cycle cost, availability, dependability, etc. In order to identify the disciplines/sciences needed to measure and predict affordability, one must examine all of the key attributes which contribute to system effectiveness.

Physics and Process Based Modeling and Simulation in VSLCD

Product (both system and subsystem) models are the key to understanding the physical interactions among various pieces of a complex engineering system. These models often take the form of structural, thermal, fluid flow, or similar physics-based simulation and analysis capabilities. In contrast, process (both system and subsystem) models focus more on the processes in which the product is involved and capture the process impact on various design objectives. Such processes can encompass manufacturing, economics, maintenance, etc. Many of today's existing product and process models were developed and have matured in a single, focused disciplinary area (e.g. legacy codes). They are often slow, require significant user interaction, and are difficult to incorporate into an integrated synthesis process. In other cases, models required for system synthesis might not exist at all. Furthermore, adequate tools rarely exist that facilitate constraint propagation to the level of assessment. Thus, one of the fundamental elements needed in the formation of VSLCD is the development of physics-based models of key responses and/or constraints as a function of design variables. These models must be efficient enough to be integrated into a sizing/synthesis program.

A synthesis and sizing tool is, by definition, a multi-disciplinary and can be visualized as a number of analysis modules linked via a geometric modeling and mission analysis core as shown in Figure 8. A hierarchical architecture is shown in the figure. In the first level, the geometry and mission core is supplemented by first level guesses, estimates, and historical trends during conceptualization (e.g., L/D estimates). The next level consists of departmentalized first-order methods of low-fidelity analysis based on a minimum configuration description (e.g., panel methods). These analyses possess a high degree of variability in their solutions due to oversimplifications and failure to capture complex phenomenon currently only discovered downstream in the design process. These methods are frequently combined into a synthesis and sizing tool or executed as off-line analysis and implemented as table-lookups.

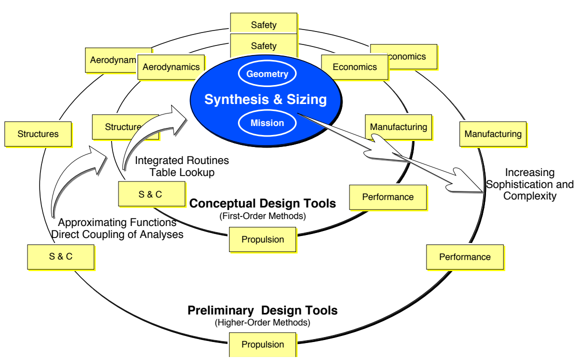


Figure 8: Varying Fidelity of Synthesis and Sizing

To correct problem accuracy and to reduce variability, higher order methods can be used for more detailed analysis (e.g. computational fluid dynamics). Though more accurate, these methods require more problem setup and analysis time with fewer iterations. Current industry practice is to reserve their use for downstream design processes. To mitigate this effect, the proposed methodology includes statistical techniques to construct metamodels of the physics-based product tools as a function of the most important variables and integrating the approximating functions (e.g. response surface equations, fuzzy logic, neural networks) into the aircraft synthesis and sizing code. The representation of process models requires heuristic approaches such as expert systems. The resulting tools give a designer the benefit of using higher fidelity information in earlier design decision-making. There are at least two additional benefits gained from using approximations. The design space region of interest is continuous, allowing for robust design and simulation techniques to be used. Second, computational cost is reduced to the evaluation of algebraic expressions. As a final note, the approximations need to be well suited to integration into an overall synthesis framework or strategy. Key features of design-oriented models are robustness, flexibility, repeatability, minimal internally generated numerical 'noises', built-in sensitivity analysis capability, and a capability to be automatically executed (batch-style or little user interaction).

Decision Support in VSLCD

During a life-cycle design process, customer requirements are transformed into a marketable solution. Moreover, the formulation of the problem will change as knowledge about a product is acquired and decisions are made. The evolution of a design is depicted in Figure 9. This formulation is multi-level and hierarchical as complex problems are decomposed. Multidisciplinary and partitioned problems require the coexistence of multiple decision-making processes that are performed simultaneously. This represents the subsystem problem solution which occurs as product design moves from conceptual through preliminary and into detail design. Problem management requires an explicit decision-support process. At each product evolution milestone, any of a number of decisions are possible, and the actual selected set of decisions forms a path.

Decision Support Environment

Design decision-making is organized into discrete milestones. These milestones are depicted in Figure 10 as specific steps in product evolution. At each milestone, a decision-making process occurs as represented by the decision path in the breakout located at the bottom of the figure. Each node of the decision path represents a candidate decision to be made by a designer. One mechanism for describing a decision is in terms of a utility function. The utility function provides a gauge of product usefulness for a decision. Finally, decisions guide product development and, thus, the allocation of resources to further decrease ambiguity in a design. These resources are deployed through modeling and simulation.

One governing metric needed by a designer to assess overall improvements with respect to customer and engineering requirements and methods to include independent sub-system decisions is a multivariate utility function. Since the problem under consideration contains uncertainty, the specialized von Neumann-Morgenstern expected utility formulation is appropriate for investigation over deterministic utility theory [2].

A precise mathematical problem is proposed in order to have the capability to calculate, at an instant in time, the utility and constraint functions which are requisite to the execution of the decision making strategy. At any instant in time, the utility of a design can be computed based on the current state with respect to the side constraints. In turn, the time history of utility is used to allocate resources in the design process. In fact, robust design may be viewed as a subset of utility.

Decision Trees

Finally, the milestones in the decision path can be organized into a decision tree. Decision trees are useful in the absence of crisp mathematical formulations during the initial phases of decision making, allows addressing the various attributes and decision steps in a fuzzy, probabilistic, and multi-variant manner. In conceptual design, little is known about a design; decisions are made based on system level metrics and sub-system approximations. It is here that concept selection must be made in the presence of a high degree of ambiguity. The risk is that it may be too expensive to transition a number of alternatives to preliminary design but potential payoffs may be lost or costly redesign incurred if a viable alternative is disregard in favor of an unfeasible concept. As decisions are made, a design progresses into later stages and similar arguments are encountered at product sub-system and component levels.

Integration in VSLCD

Engineering simulation via a virtual design environment is a key part of the proposed architecture. The architecture must sufficiently mask computing technologies as to promote decision-making based on the ideas discussed here. Information technology plays a significant role in the preliminary implementation the authors have developed. Key technologies have been devised that facilitate the integration and simulation of the elements of VSLCD and are based on accepted Internet practices where applicable.

Agents are a key facilitator of VSLCD and are programmatic objects which facilitate the integration, whether direct or through approximating functions, of product and process based analysis models [23]. Designers benefit from agents due to the repetitive and monotonous task of program execution and data archiving is automated. Models are directly combined into agents and then linked to the architecture. The linking is accomplished via a 'wrapper' which provides a transparent gateway to computing services such as communications, name service, and platform support. Earlier discussions highlighting mechanisms for integration of first and higher order physics-based as metamodels are depicted in Figure 11 as they relate to agents. One or more of these techniques is used to implement each of the required analysis into the architecture.

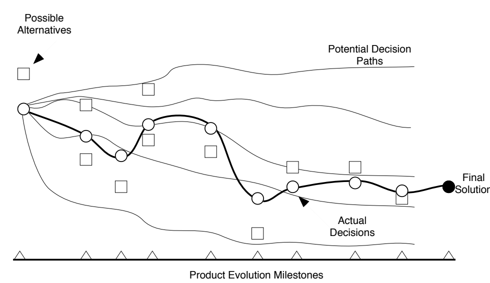


Figure 9: Decision-Support for Product Evolution

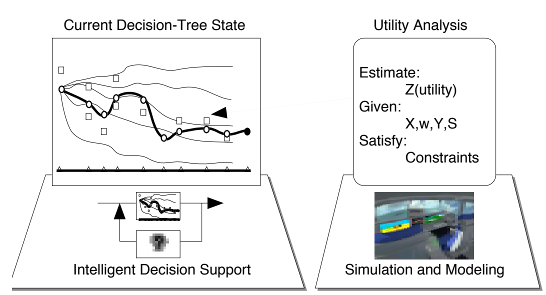


Figure 10 : Decision-Making Milestone and Its Solution

Figure 12 : Feasibility and Viability: The Need to "Shift the Curves"

space is shown in Figure 13. This probabilistic methodology identifies feasible and viable design alternatives and proposes the introduction of new technologies to increase feasibility, if needed.

Step 1. Define the Problem to be Tackled Identify objectives, constraints, design variables (and associated side constraints), analyses, uncertainty models, and metrics for each discipline and for the system level. This involves translating the customer requirements to the items listed.

Step 2. Determine System Feasibility At this stage of the design process, an optimum is not desired. Instead, an estimate of the percentage of the design space which contains feasible alternatives is important. If there is minimal or little chance of obtaining a feasible design, there is no use in searching for optimal or robust solutions.

Step 3. Investigate Active Constraints If the system achieves an acceptable *P(feas),* then proceed to Step 5. If the system achieves an unacceptably low (or zero) *P(feas),* an investigation must be performed to find out which constraints are active and most restrictive. Crisp definitions for the fuzzy modifiers “acceptable” and “unacceptably low” are at the discretion of the designer.

Step 4. Infuse New Technologies The infusion of new technologies may be required to improve the *P(feas)* value. New technologies almost always affect the underlying physics of the design space and not necessarily the geometry of the space itself, as defined through the design variable ranges. These effects may be beneficial with regards to one metric while detrimental to another. For example, increased use of composites might reduce weight while at the same time increasing the vehicle’s cost of manufacture.

Step 5. Robust Design Simulation (RDS) [1] Steps 1-4 above are concerned with feasibility, since only constraints are considered. When a large enough feasible space is found, the space can be searched for robust solutions. RDS is a systematic procedure for finding settings of design variables which maximize the probability of meeting or surpassing a target for the objective, while satisfying the constraints.

Robust Design Using Probabilistic Techniques

Robust Design Simulation (RDS) is the part of VSLCD (Figure 7) where system level analysis takes place, while accounting for uncertainty, business practices, economics, synthesis and sizing, technology, and environmental constraints. Application of RDS can be found in [1, 6, 14, 21, 25]. A principle advantage of this construction is that it gives the designer the ability to concurrently consider the aforementioned aspects of design at the conceptual level. The premise behind robust design is that the best way to achieve customer satisfaction is to deliver a product that performs well not only in the environment for which it was designed, but in all environments. Design for robustness is achieved by finding settings for control parameters which will not only maximize mean performance in some sense, but also minimize the objective function variance and satisfy all constraints. This is accomplished in RDS by incorporating all elements essential to the success of the design into an overall framework, with the ultimate goal of affordability which is insensitive to changes in external noise factors.

Under the RDS, an initial statement of robust design optimality is as follows. Note that since the noise parameters are typically described in terms of probability distributions, it is intuitively obvious that the output from this mathematical model must also be a distribution.

maximize *s = fcn(mean and variance of Z(X,Y)) or* *Prob*$(Z(X_i, Y_j) < z_o)$

given *Z = Overall obj. (measure of merit) = fcn (X,Y)*
X_i *= vector of i deterministic variables*
Y_j *= vector of j uncertain variables, defined by uncertainty models* Ω_j
z_o *= Target (a particular value of Z) supplied by the customer/decision maker*

satisfying *imposed constraints, design space ranges*

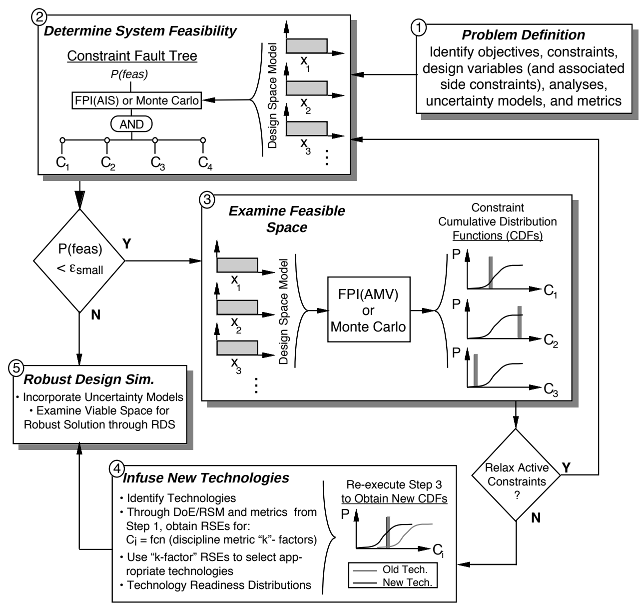


Figure 13 : Investigating Feasibility and Viability of Multidisciplinary Systems

A flowchart for how one would setup and solve this problem in RDS is illustrated in Figure 14. Traditionally, design is comprised of a simulation code (sizing/synthesis or economic analysis) and an optimization routine which varies the design parameters to yield an "optimum" solution subject to all imposed environmental and design constraints. On the other hand, RDS uses the synthesis tool along with constraints to perform a probabilistic analysis that yields a figure of merit as a measure of robustness (e.g. objective function response *(R)* mean and variance [26]). This figure of merit is associated with a probability distribution rather than a single point design solution as is the case with traditional methods [1].

One of the major obstacles in applying probabilistic methods is to accommodate the large variety of existing deterministic computer codes used in modern systems design. A generic methodology is proposed, which utilizes a 'wrapper' that, when linked to the selected analyses codes, drives the program and yields the desired results. Based on this formulation, probability functions can be assigned to each of those input variables which are considered to be uncertain and a cumulative probability distribution function for each of the desired objectives may subsequently be obtained. Most probabilistic analyses, e.g. MC Simulation [27], estimate their probability distribution functions based on a large number of samples generated over the design space, defined by the random variable ranges.

The use of computer tools allows for an easy perturbation of input values. However, computation time to achieve a probabilistic result increases significantly as design complexity increases. Three methods that incorporate such complex computer programs in a probabilistic systems design approach have been described by Fox[7] and are shown in Table I. The use of metamodels has found the widest application and has also been used in the past [1, 6,14,21,25,26,28, 29]. The use of statistical regression models, based on Taylor series expansions, along with experimental designs is very popular [1,6,14,25,26,28,29,30,31,32].

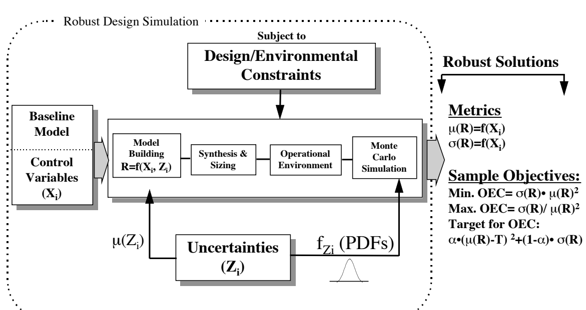


Figure 14 : Implementing the Robust Design Simulation (RDS)

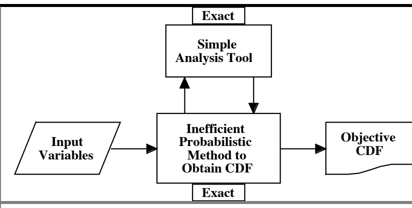
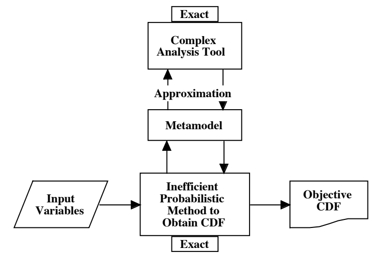
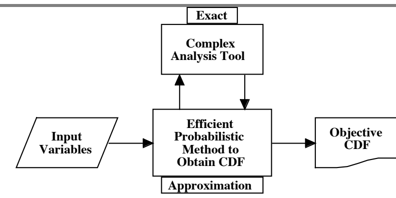
Concluding Remarks

Present day design practices rely heavily on the incremental changes and improvements of existing designs. This approach has been quite successful because risk, controversy, and negative impact have all been mitigated through iteration. However, achieving significant design advances, as in the case of new innovative, out-of-the-box thinking concepts, requires innovative design and technological improvements. These advances come at the price of increased risk and uncertainty.

A paradigm shift from performance-based analysis to design for affordability is required to bridge the gap from evolutionary design to revolutionary systems. Tremendous payoffs can be achieved if this shift occurs. Cycle-time reduction, minimal variance designs, robust solutions, and affordable systems are a few of the perceived benefits. A multi-disciplinary, life-cycle emphasis must be considered if this shift is to occur. This includes a mechanism for ascertaining design and operational uncertainty, including requirement ambiguity, analytical tool fidelity, decision making in the presence of conflict and risk, and the ability to forecast and assess impact and readiness of new technologies.

The authors have proposed a formulation for Virtual Stochastic Life Cycle Design that has piecewise been successful in making the paradigm shift. VSLCD provides the ability to infuse new, "breakthrough" technologies into the design process and evaluate their impact in terms of benefit, cost, and risk even before the time and expense of developing and maturing this technology is complete. Information modeling provides the foundation for representing uncertain, ambiguous, and deterministic variables are represented. VSLCD includes physics-based modeling and simulation to allow high-fidelity accuracy to be combined with sizing and synthesis tools. This creates a multi-disciplinary environment with minimal impact on design time. Agent technologies provide integration models that make the modeling possible. Finally, design decisions are supported by utility functions as a top-level metric for assessing design progress and subsequent resource allocation. Robust design is a necessary component of the utility function, and is calculated using probabilistic methods. These techniques are combined with a five step feasibility/viability process to enable the determination of affordable systems.

Table I: Code Integration for Probabilistic Analysis

Probabilistic Analysis Through Direct Coupling Analysis tool is used in for each calculation of a Monte Carlo Simulation ***Advantages:*** Direct analysis results ***Disadvantages:*** Time consuming analysis	
Metamodel Based Probabilistic Analysis Metamodel is used to approximate design code and linked to Monte Carlo Simulation ***Advantages:*** Reduced simulation time, straightforward integration ***Disadvantages:*** Metamodel may be statistically inaccurate, limitation in number of variables	
Metamodel Based Probabilistic Analysis Actual design code is linked to approximate metamodel of Monte Carlo Simulation ***Advantages:*** Reduced simulation time, direct analysis results ***Disadvantages:*** Distributions are approximated	

Future efforts are focused on providing expanded work on utility as a governing function, and its associated probability developments and design guidance through simulation and soft computing technologies.

Acknowledgments

The authors wish to thank NASA Langley-Systems Analysis Branch (NAG-1-1793), NASA Ames-Systems Analysis Branch (NAG-2-1047), and the Office of Naval Research (ONR) for continuing support of this research. The author's would also like to graciously thank Michelle R. Kirby for her contributions to this paper.

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